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Valuation of ethnic diversity: heterogeneous effects in an integrated labor and housing market

*Jessie Bakens**,† *and Thomas de Graaff***,***

*Research Centre for Education and the Labour Market, Maastricht University, The Netherlands
**Department of Spatial Economics, VU University Amsterdam, The Netherlands
***Tinbergen Institute, Amsterdam, The Netherlands
†Correspondence to: *email* <j.bakens@maastrichtuniversity.nl.>

Abstract

We estimate the heterogeneous impact of the scale, composition and consumer good effect of ethnic diversity on individuals' job and residential location. Using an extensive pooled micro panel data set in which homeowners in the Netherlands are identified in both the housing and labor market, we can derive the combined effect of ethnic diversity in both markets. We test a model that integrates the utility and production function such that the location of work and residence is determined simultaneously by taking into account observed and unobserved heterogeneous individual behavior on both markets. We find that the scale of ethnic diversity, that is the share of immigrants, at the city level is mostly positively related to both wages and house prices. This is mainly through a positive productivity effect of immigrants, which results in negative implicit prices for housing (although small) in a city with a higher scale of ethnic diversity for the majority of the individuals in our data. The scale of ethnic diversity is only positively related to utility for a small group of homeowners, while the composition (diversity among immigrants) and the consumer good-effect (ethnic diversity of restaurants) of ethnic diversity show overall no significant effect on both markets nor significant implicit prices. Moreover, we find that the majority of Dutch homeowners do not sort themselves out over municipalities by their preferences for ethnic diversity.

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JEL classifications: R12, R23, R3
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1. Introduction

Many European countries are experiencing a rapidly changing population composition, resulting in increased diversity associated with new and growing immigrant groups. Whether the impact of diversity on economic outcomes is positive (a diversity dividend) or negative (a diversity debit) is still very much a matter of empirical debate (see, e.g. Kemeny, 2014). In general, there is evidence that, at least for specific types of firms (mostly large, multinational and high-tech firms) or specific types of workers, a moderate amount of diversity seems beneficial for productivity and innovativeness (see, e.g. Docquier et al., 2013; Ozgen and de Graaff, 2013; Peri et al., 2015; Trax et al., 2015; Nathan, 2016; Kemeny and Cooke, 2018). For residential-specific preferences of workers, an increase in immigrants may positively impact house prices and rents due to a demand–effect (see, e.g. Saiz, 2003, 2007; Saiz and Wachter, 2011; Sanchis-Guarner, 2013). However, the empirical evidence on the effect of diversity on utility-related measures of location-specific preferences of workers is much scarcer and points toward a small effect with varying sign, depending on the level at which location preferences are measured (cities, neighborhoods, etc.) (see, e.g. Ottaviano and Peri, 2005, 2006; Bakens et al., 2013).

Most of the research focuses on the average effect of diversity on economic outcomes. In this article, we test the hypothesis that the utility derived from living or working in ethnically diverse cities[1] differs among individuals. We argue that most studies that look at the average effect of a diverse population on the local economy forgo important individual-level variation in these effects. If the working population consists of individuals whose preferences for ethnic diversity differ, then spatial sorting is likely to occur in the presence of spatial differences in ethnic diversity. As is shown in Combes et al. (2008) and Bakens et al. (2013), individual characteristics are an important factor in explaining productivity differences between individuals, and the subsequent sorting of workers over regions. Workers locate in an area that gives them the highest real utility, which from a regional equilibrium point of view, is based on the trade-off between nominal wages, the costs of housing and preferences for (residential) amenities (Rosen, 1974; Roback, 1982). The empirical question is to what extent the effect of ethnic diversity prevails in this trade-off between the labor market and/or the housing market. The effect on the former involves productivity externalities caused by ethnic diversity in firms or the local labor market. The effect on the latter involves changes in utility from local ethnic consumer amenities, such as a more diversified supply of products and services.

In research on the economic impact of immigrants on receiving regions, the focus on the productivity effect is mostly prevailing. Based on the idea of immigrants' skills complementarity in production, more immigrants or more diverse immigrants may increase productivity (for a more detailed description of the mechanisms, see Alesina et al., 2000). In addition, there may also be counter effects of more diversity if this hampers, for example, communication (Lazear, 1999). In the research that tests these hypotheses, the scale (teams, firms, regional labor markets) at which these effects may occur is an important research question (Trax et al., 2015; Nathan, 2016; Kemeny and Cooke, 2018), but also how to measure this complementarity in terms of diversity measures (see for recent discussions on the measurement of diversity, Nijkamp and Poot, 2015; Desmet et al., 2017). Generally, measures are used that focus on the number of workers from different ethnic or cultural groups, and the size of these groups. In this research, we focus on a scale effect (the immigrant share), and a composition effect (the diversity among immigrants), following Ottaviano and Peri (2006), Alesina et al. (2016) as a city can be more diverse if there are more immigrants, and be more diverse if there are immigrants from a larger number of different countries.[2] We distinguish these two population effects to disentangle whether it is the number of immigrants that may impact productivity or utility, or whether it is their composition that matters. In addition, we include a third measure of ethnic diversity, a consumer good-effect measured by the ethnic diversity of the cuisine of restaurants. With the increase of

1 This analysis focuses on municipalities, which in the remainder of this article we will refer to as cities.
2 We define these measures in Section 4 and in Supplementary Appendix Table A1. Following the Statistics Netherlands' definition of an immigrant, both the first- and second-generation immigrants are included.

immigrants in an area, the area is likely to become more diverse in terms of consumer goods supplied. This stems from immigrant's consumption patterns, but also their supply of other goods as entrepreneurs (see, e.g. Waldfogel, 2008; Mazzolari and Neumark, 2012; Pekkala Kerr and Kerr, 2016). If consumers value local product heterogeneity (Dixit and Stiglitz, 1977), as is argued to be an attractive feature of cities by Glaeser et al. (2001), then immigrants may increase consumer's utility. We jointly evaluate these three diversity measures in the labor and housing markets to research whether these effects dominantly relate to productivity or utility effects.

Figures 1 and 2 give the quartile distributions of incomes and house prices depending on the immigrant shares, the diversity among immigrants and diversity of restaurants in a city. Indeed, at first sight, it appears that the distributions of income—albeit moderately—and house prices correlate with the upper quartiles of the scale, composition and consumer good effect of ethnic diversity. If individuals sort into cities with different ethnic amenity endowments, then it is not *a priori* clear which individual characteristics may lead to these different valuations of ethnic diversity. We therefore adopt an empirical approach in which we assume that differences in valuation of ethnic diversity can be inferred based on a worker's simultaneous behavior in both the housing and labor market and his or her preferences for amenities (following Roback, 1982). We do so by estimating a multivariate latent class model. This enables us to identify subgroups in the data as well as the simultaneous decisions of workers in both markets without prior knowledge about the individual characteristics that cause these differences. Consequently, an *ex post* facto description of the differences between subgroups in terms of the characteristics of individuals provides insights into drivers that may determine to which subgroup an individual belongs.

The main contribution of our article to the literature is 3-fold. First, our approach overcomes the methodological issues inherent in most research on this topic that depends heavily on the specific subsample chosen or are focused on the 'average' effect. The latter issue is concerned with the fact that it is either assumed that all individuals benefit equally from ethnic diversity or that specific homogeneous groups of individuals are sampled to control for possible variation in the impacts (see, e.g. Florida, 2002; Ottaviano and Peri, 2005, 2006; Dalmazzo and de Blasio, 2011). The usual approach to account for possible heterogeneity in the effects is to use individual fixed effects. This approach controls for (un)observed individual characteristics that might determine differences in utility and preferences.[3] However, it is precisely these (un)observed heterogeneous individual characteristics that play an important role in explaining the individual differences in wages and utility (Bakens et al., 2013). Thus, disregarding individual variation in characteristics by focusing on the average effects of ethnic diversity on wages and utility very likely provides a misguided view of the effects of ethnic diversity on specific population groups. By using a finite mixture model, no pre-determined samples of individuals need to be made, but effects can be estimated over different groups within the model. Although there is related research in which Ozgen and de Graaff (2013) and Nathan (2016) apply finite mixture models to analyze the effect of (ethnic) diversity on productivity and innovation, and Kemeny and

3 In many papers, correctly controlling for unobserved heterogeneity among individuals is a challange. The recent paper by Kemeny and Cooke (2018) uses matched employer–employee data from the USA to control for unobserved heterogeneity among individuals.

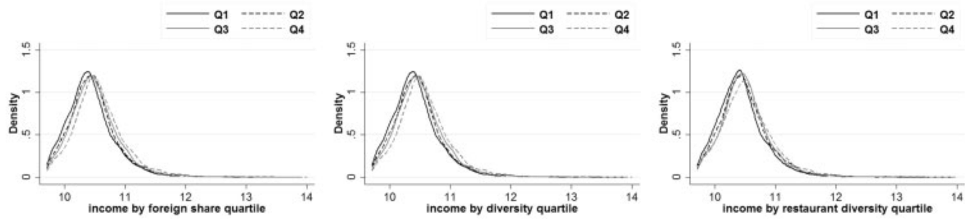

Figure 1. Distribution of income over (ethnic) amenity quartiles at the city level.

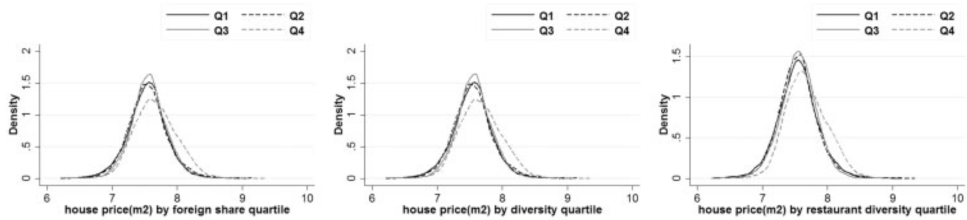

Figure 2. Distribution of house prices (per square meter) over (ethnic) amenity quartiles at the city level.

Cooke (2018) analyze the effect of ethnic diversity on productivity along wage quartiles, we are not aware of other research that explores heterogeneous effects of population diversity on individual utility.

Secondly, by using a theoretical framework based upon Roback (1982, 1988), we show that failing to account for unobserved heterogeneity simultaneously in both labor and housing markets results in biased estimates of the impacts of diversity on wages and utility. Our empirical analysis indeed shows that estimating wage and housing prices separately yield different results when compared with our simultaneous estimation.

Finally, we employ an extensive micro dataset consisting of a pooled cross-section of administrative income and housing data between 1998 and 2008 in the Netherlands. This data focus on homeowners in the labor and the housing market. The micro-data allow a simultaneous estimation of an individual's correlated choice of location of living and work and we explicitly allow individuals to work and live in different cities. Relaxing the assumption that the amenity endowment in the area of work is equal to that of the area of residence accommodates the empirical setting in many countries, especially in the Netherlands, where half of the workers do not live in the same municipality in which they work. Because we use a pooled cross-section instead of panel data,[4] this article is focused more on estimating possible heterogeneity in correlations for different individuals than on causal effects.

To anticipate our results, we find four different homogeneous groups in our data in terms of the valuation of ethnic diversity. There is one large group, which includes

4 There are repeated observations for a specific subset of our data. However, only selecting homeowners who move at least twice in 10 years, gives a more specific subsample of individuals than only homeowners who moved between 1998 and 2008 and may therefore give biased results.

almost 72% of the individuals in our data set, and three smaller groups. The groups differ in terms of their location patterns, with the smaller two groups clustering in and around the largest cities in the country and the other small group clustering in the periphery of the Netherlands. The largest group is more dispersed over the country. For most individuals in our data set (the large group and two other small groups), we find a positive and statistically significant correlation between their productivity and the scale of ethnic diversity, in that both the wages and rents are higher for these individuals if the immigrant share in the city of work and city of residence is higher. For a small group of individuals, we find a statistically significant utility effect of the scale of ethnic diversity. The group that is concentrated in areas with fewer immigrants shows a positive correlation between the utility and the share of immigrants, while the group concentrated in and around the largest cities of the Netherlands show a negative correlation between their utility and the share of immigrants. For the composition and the consumer good effect of ethnic diversity, we do not find a jointly statistically significant correlation between the labor and housing market outcomes for most of the individuals in our data set. The dominance of one large group, with smaller groups that show different results, and the prevailing positive effect of the share of immigrants on productivity holds against various robustness checks. A welfare analysis shows that the implicit prices for higher (or lower) immigrant share, immigrant diversity and restaurant diversity are very moderate. For most individuals in our data set (ethnic), amenities do not play a large role in explaining location patterns.

The remainder of the article is organized as follows. The next section presents explicitly our assumptions in combination with a theoretical equilibrium model describing the location choices of individuals based on local amenities in the labor and housing markets. We discuss the estimation of a finite mixture model in Section 3. Section 4 describes the data we use in our empirical analysis. Section 5 gives the results and postdescriptives of the groups we identify using the finite mixture model. Subsequently, Section 6 discusses the results of various robustness checks. The last section concludes.

2. Modeling framework

To assess the heterogeneous valuation of ethnic diversity, we adopt a spatial equilibrium modeling framework where heterogeneous households and firms sort over municipal amenities. We first describe such a polycentric urban system, and then construct an empirical model that is able to account for differences in workers' preferences and firms' cost structures with respect to varying endowments of amenities and lose the restriction that workers and firms have to be located in the same location.

2.1. Heterogeneous returns to diversity within a polycentric urban system

We consider a closed spatial system, where cities ($s \in 1, \ldots, S$) are characterized by varying endowments of a set of exogenous amenities (θ_s). We consider the endowments of land and the supply of housing as fixed. Amenities can only be consumed or used as a production input locally, but we do allow for commuting between cities.[5] Within cities,

5 More realistically, we could assume that transportation costs for labor are lower than for amenities.

the landscape is considered homogeneous, so there are no intra-city commuting costs (see, e.g. Glaeser, 2008). We assume that workers are homogeneous apart from their preferences for amenities. Analogously, on the demand side, we assume that firms differ in the productivity effects of amenities. Apart from this, firms are similar and both produce a final good x.

To understand what happens when a location becomes more amenable, Figure 3 depicts the three possible resulting outcomes for the simplest case of a specific city with homogeneous types of workers and firms, and only one amenity (conform Roback, 1982, 1988; Ottaviano and Peri, 2005). Consider location A where workers receive wages ω and pay rents r in a city with a specific amenity endowment θ leading to a generic cost level $\underline{c}$ for firms and utility $\underline{k}$ for workers. We consider an exogenous increase of the amenity endowment θ. If amenity θ is both amenable to firms and workers, then the only possible new outcome—with zero moving costs for firms and workers—would be location D, with higher rents and an ambiguous change in wages. Which means that the city becomes more attractive to workers and firms, leading to higher rents, and firms are willing to pay higher wages while workers accept lower real wages. Consequently, if the amenity is only amenable to workers and not to firms, the new location would be B with lower wages and higher rents. In the case only firms benefit from the increase in θ and not the workers, the new location would be C, where both rents and wages increase.

The model described above is not in line with at least three stylized facts. Firstly, cities differ from each other in combinations of multiple amenities. Second, commuting yields different amenities for places of work and places of residence (especially in polycentric city structures). Third, firms differ in the impact of amenities on their cost structure (if not only by sector) and workers differ in the impact of amenities on preferences. Note, that if we only allow for heterogeneity in workers' preferences and firms' cost structures with respect to varying endowments of a single amenity, then perfect sorting would occur. In combination with commuting and multiple amenities, however, perfect sorting for one amenity is less likely and combinations of firm and worker types in the same location could occur.

Therefore, we extend the model in three ways. Firstly, we allow workers and firms to benefit from multiple amenities. So, we regard θ_s as a city-specific set of amenities. Second, we introduce heterogeneity in workers' preferences and firms' cost structures. Some workers may have a preference for ethnic diversity, while others might have strong preferences for natural amenities. We therefore model different preferences among workers (so for workers of type i, it is $U_i(\theta_s)$) and different cost structures among firms (for firms of type j, it is $C_j(\theta_s)$). Note that this notation is deliberately very general and allows for city-specific preferences and cost structures as well, regardless of the size of the amenities. Due to social network structures, workers and firms might be tied to a specific city. Finally, workers do not necessarily have to live in the city where they work. Especially for a country such as the Netherlands, with its polycentric structure, commuting is very important.

These three extensions yield a more complex and realistic trade-off than the traditional set-up. Because workers are heterogeneous and multiple amenities might play a role, workers with different preferences who pay similar rents and receive similar wages could still have similar indirect utility levels. Additionally, if cities become too expensive for some workers, then they opt out by commuting into the city, whereas they pay lower rents but receive lower wages (net of commuting costs) as well. For firms, a

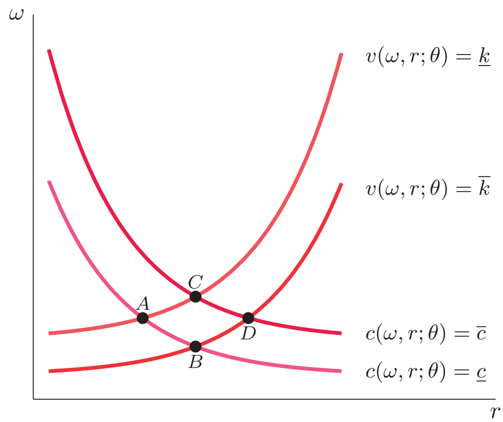

Figure 3. Changes in wages and rents with varying amenity endowments.

similar reasoning holds. The next subsection describes how we extend the seminal Roback (1982) model with these three elements.

2.2. Modeling a polycentric urban system with varying amenities

To derive our empirical specification, we adopt the framework of Ottaviano and Peri (2005) which itself builds on earlier work of Rosen (1974), and Roback (1982, 1988). Specifically, we extend Ottaviano and Peri (2005) by allowing for commuting and heterogeneous workers and firms. The heterogeneous preferences for amenities of workers of type i, living in city s, working in a firm of type j in city κ are modeled by the following Cobb–Douglas utility function:

$$U_{ijs\kappa} = \exp(\gamma\theta_{is})H_{is}^{1-\mu} Y_{ijs\kappa}^{\mu}, \tag{2.1}$$

with $\exp(\gamma\theta_{is})$ the impact of the whole set of local amenities θ in city s on utility U for workers of type i,[6] H the amount of housing workers of type i consume in s and Y a Hicksian composite good. Commuting is introduced by assuming that each worker of type i only receives monthly labor income $\overline{\omega}_{ijs\kappa}$ (wages $\omega_{ijs\kappa}$ net of commuting costs $t_{s\kappa}$)[7] which she receives from working in a firm of type j in city κ and can only spend on land and consumption goods.

For firms, we introduce heterogeneity in the production effects of amenities by using a Cobb–Douglas production function for firms of type j in city κ as follows:

$$Y_{j\kappa} = \exp(\xi\theta_{j\kappa})H_{j\kappa}^{1-\alpha} L_{j\kappa}^{\alpha}, \tag{2.2}$$

6 We model the impact of amenities exponentially. This is mainly for convenience as to avoid taking the logarithms of zero later on in the model. Models with linear impacts of amenities yield qualitatively similar results.

7 We refrain from specifying the commuting costs $t_{s\kappa}$. Our only assumption here is that between each possible city pair there are exogeneously given positive commuting costs. In our empirical specification, $t_{s\kappa}$ is measured as a loss in net wages governed by the value of travel time.

where L is the amount of labor firms of type j employ and $\exp(\xi\theta_{j\kappa})$ denotes the impact of the whole set of amenities θ in city κ on the productivity Y of firms of type j.

We consider our spatial economy in equilibrium if no worker of type i and firm of type j have an incentive to migrate. In addition, workers and firms in the same location pay similar rents, workers of type i have similar utility levels across cities (and earn similar wages within cities net of commuting costs), and firms of type j face equal costs across cities.

Note that we still allow for workers to work for different types of firms and in different cities. Moreover, this implies that workers and firms of different types do not necessarily have similar utility levels or costs levels, and firms profiting from amenities are able to pay higher wages and drive up rents in these locations.

Clearing of factor prices results in a wage and rent equation for each type of worker and firm combination. As it is impossible to observe all relevant amenities, we separate the vector of city-specific amenities in Equations (2.1) and (2.2) in a vector of observed θ^o and unobserved amenities θ^u. Moreover, if we allow for additional control variables $\mathbf{X}$ and $\mathbf{H}$, then our set-up yields the following reduced-form wage and rent equations for workers i living in city s working for firm j in city κ[8]:

$$\ln \overline{\omega}_{ijs\kappa} = \beta_1 \mathbf{X}_{j\kappa} + [\beta_2 \ln(\theta^o_{is}) + \beta_3 \ln(\theta^o_{j\kappa})] + [\beta_4 \ln(\theta^u_{is}) + \beta_5 \ln(\theta^u_{j\kappa})] + \epsilon_{ijs\kappa} \tag{2.3}$$

$$\ln r_{ijs\kappa} = \delta_1 \mathbf{H}_{is} + [\delta_2 \ln(\theta^o_{is}) + \delta_3 \ln(\theta^o_{j\kappa})] + [\delta_4 \ln(\theta^u_{is}) + \delta_5 \ln(\theta^u_{j\kappa})] + \mu_{ijs\kappa} \tag{2.4}$$

If there are relevant and unobserved amenities such as the ones between the second pair of square brackets (θ^u_{is} and $\theta^u_{j\kappa}$) in Equations (2.3) and (2.4), and if they correlate with the observed amenities or with the other explanatory variables ($\mathbf{X}_{jk}$ and $\mathbf{H}_{is}$), then it is straightforward to see that failing to account for unobserved amenities that affect utility or production leads to biased estimates in both the wage and the rent equation. Without appropriate instruments for both θ^o_{is} and $\theta^o_{j\kappa}$, it is therefore crucial that the rent and wage Equations (2.3) and (2.4) are estimated simultaneously, and the unobserved heterogeneity bias in both equations is properly accounted for.[9] In the next section, we lay out the methodology to do this.

3. A Multivariate Finite Mixture Model

We estimate Equations (2.3) and (2.4) by adopting a latent class model in the form of a multivariate finite mixture model. In a finite mixture model (FMM), the allocation of individuals to groups is defined within the model estimation (see McLachlan and Peel, 2000). The different groups, or classes, are thus not defined *a priori* based on the

8 Apart from introducing heterogeneity and commuting costs—and its implications for the spatial equilibrium—the model does not deviate in its mechanics from that of Ottaviano and Peri (2005). For more details, we therefore refer to their paper.

9 The most common approach is to use instrumental variables that correlate with amenities (in our case ethnic diversity), but are independent from both the labor and the housing market. Unfortunately, these are very hard to find and even deep-lagging—for example, looking at the population structure in the past—might not necessarily yield instruments that are independent from both wages and rents conditional on current population structure (see Deaton, 2010). A fruitful future approach might be to look at the location patterns of refugees as their location choices are typically severely limited—at least in the short run. Unfortunately, our data does not capture refugees.

observed characteristics. Moreover, a multivariate finite mixture model makes it possible to deal with the fact that choosing where to work and where to live are correlated decisions in which observed and unobserved individual characteristics affect both decisions. The result is a number of groups that differ in terms of observed characteristics between the groups, while within the groups individuals are considered to be homogeneous in their preferences.

In our model, we make three specific assumptions. First, we assume that individual and housing characteristics have a generic effect on wages and rents while preferences for amenities have a heterogeneous effect on wages and rents. As shown in Equations (3.1) and (3.2), we thus assume that individual characteristics affect wages, and housing characteristics impact housing prices homogeneously across all individuals in our sample, while the effect of amenities is considered to be heterogeneous.[10]

Second, we assume that the observations are taken from a population that is a mixture of z homogeneous groups with mixing proportions (McLachlan and Peel, 2000). We do not know, *a priori*, from which group we observe wages ($\ln \overline{\omega}_{ijs\kappa}$) and housing prices ($\ln r_{ijs\kappa}$).

Finally, following the theoretical specification of Roback (1988), we allow the housing and labor market to be correlated by strictly imposing that the composition of the groups for the labor and housing markets is similar, that is, if a worker is part of a specific group in the labor market, then she is also part of that same specific group in the housing market. This allows us to control for unobserved heterogeneity in the preferences among different groups in both the labor and the housing market.

We simultaneously estimate the following system of equations:

$$\ln \overline{\omega}_{is\kappa t} = \beta_{0,z} + \beta_1 \mathbf{X}_{i\kappa t} + \beta_{2,z} \ln(\theta_{\kappa t}) + \xi_t + \epsilon_{is\kappa t} \tag{3.1}$$

$$\ln r_{ist} = \delta_{0,z} + \delta_1 \mathbf{H}_{ist} + \delta_{2,z} \ln(\theta_{st}) + \psi_t + \mu_{ist} \tag{3.2}$$

where $\overline{\omega}_{is\kappa t}$ is the wage—net of commuting costs—of individual i living in city s and working in city κ in year y, and r_{ist} is the housing price per square meter of individual i living in city s in year t. The coefficients related to the vector of individual characteristics in the labor market, β_1, and the set of dwelling characteristics of individual i's house, δ_1, are homogeneously estimated. The following individual characteristics are included in $\mathbf{X}$: education level, age, sector of employment, household type, a dummy for males, a dummy for an individual member of a double-income couple, and a dummy for natives. The following dwelling characteristics are included in $\mathbf{H}$: the number of rooms, the type of dwelling, the construction period, a garden dummy and a dummy for good maintenance. The constant terms, the coefficients corresponding to the vectors of amenities $\theta_{\kappa t}$ and θ_{st}, are allowed to be specific to group z. Because we do not know, *a priori*, which amenities affect individual preferences and firm productivity, we consider the same set of amenities for both regressions. To control for year-specific effects, we include year dummies ξ_t and ψ_t. Finally, μ and ϵ are the error terms, which are assumed to be correlated because the decision regarding the

10 Because we are predominantly interested in differences in preferences for amenities, this assumption greatly simplifies our estimations. However, it can be argued that the effect of age or sector of employment on wages might be heterogeneous and that preferences for housing characteristics differ. Here, we aim to control only for the individual and housing characteristics on wages and house prices, respectively.

location of work and the location of residence are made in tandem or because one restricts the other as explained above.[11]

We use a multivariate finite mixture model to estimate Equations (3.1) and (3.2) simultaneously.[12] A finite mixture of regressions assumes that the observations in a data set can be from z different groups, with each group following a different parametric distribution. The maximization of the log-likelihood function is implemented using the iterative expectation maximization (EM) algorithm (Dempster et al., 1977). In the first step (E-step), the expected value of the complete log-likelihood function with respect to different groups is computed at the current estimate of the parameters. Because there is no straightforward way of distinguishing the different groups, this step calculates the posterior probability of individual i belonging to group z. The second step (M-step) maximizes the log-likelihood of the function derived in the first step. The regression coefficients for each group are estimated using the probability weights for that group for all individuals and are then used to determine the expected value of the complete log-likelihood function in the next E-step. This procedure iterates until convergence is achieved.

4. Data

Our analysis is based on a data set that contains observations of individuals in the labor and the housing markets in the Netherlands. The data consist of house transaction prices between 1999 and 2008, which are provided by the Dutch Association of Real Estate Agencies (NVM). The house transaction data include information on the transaction date, transaction price, dwelling characteristics and location.[13] About 50–70% of all residential houses sold in the Netherlands are registered by NVM, with a slight oversampling of the more populated areas of the Netherlands. For each house sold, the owner of the house is identified using administrative municipality data from Statistics Netherlands. Each adult (maximum of two per house) who has an income from (self-)employed work and who moved to the address within 9 months of the date, the house was sold is included in the data set.[14] We only include individuals that stay

11 Both wages and housing prices are in constant 2008 prices.

12 We refer to McLachlan and Peel (2000), Grun and Leisch (2008) and Wedel and Kamakura (2012) for detailed information on finite mixture model estimations. For the estimation procedure, we use the flexmix package developed in R by Grun and Leisch (2008).

13 We only select transactions between €30,000 and €15,000,000 in constant 2008 prices and with a minimum floor area of 30 m^2. Additionally, houses sold for more than twice or less than one-third of the initial offer price are excluded.

14 We do not perform the analysis on households or household heads because, in general, in the Netherlands if a couple has two incomes, both incomes are used to obtain a mortgage and therefore the individual characteristics of the labor and housing markets of both matter. Van der Straaten and Rouwendal (2010) studied the co-location decisions of the so-called power couples in the Netherlands and found that proximity to dense labor market areas, railway stations and urban amenities is more important for double-income couples than for average households. In the analysis in this article, we include a dummy variable for individuals who are part of a double-income couple. Still, the disadvantage of treating a couple as an individual decision maker is that we underestimate income in that individual rather than household income is used. As a robustness check, we also estimate the model with only single-earner households. In addition, we also check whether our results are robust when we use a homogeneous sample of males within the age cohort of 30–45. The subsample with single-earner households, and the sample with only males are much smaller than the original dataset, but show generally comparable results. The results of these estimates can be found in the Supplementary Appendix Tables A10–A15.

registered at that address for >90 days. The administrative municipality data also include individual demographic information such as date of birth, country of birth (also that of both parents) and gender.

The constructed data set of homeowners is linked to firm data to identify the work location, sector of employment and income of the homeowners. The labor market data are also provided by Statistics Netherlands.[15] For employed individuals, we obtain the yearly wage by multiplying the daily wage with an average working year of 261 days. For self-employed individuals, we use the reported yearly profit. All income is stated in constant 2008 prices. We refer to Supplementary Appendix Table A1 for a detailed description of all variables. Because we allow for commuting, we correct the yearly wage for commuting costs if the city of residence is different from the city of work. According to research on Dutch mobility (Olde Kalter et al., 2010), the average travel speed for commuting is 45 km/h (or 0.75 km/min) by car, and the average value of time is €8 per hour (or €0.133/min). Because only Euclidean distance is readily available, we multiply the distance by 1.3 to approach real distances. Considering 261 working days per year and the time spent commuting to and from work, we construct individual yearly travel time costs and deduct these from individual wages. Amenity data for each Dutch municipality, such as the number of shops, theaters, museums and restaurants, but also job and population density, and the share of highly educated workers are provided by Statistics Netherlands and the Real-Estate Monitor ('Vastgoed monitor') of ABF research.

Whereas we use house prices to identify location preferences, rents are more often used for this purpose (see, e.g. the original work of Roback, 1982, and Ottaviano and Peri, 2005, 2006). Because we only have house prices available and therefore capture the characteristics of homeowners, our sample and results are not representative of the entire population of workers. Our sample is biased because we do not capture the lower end of the income distribution, that is, that part of the labor force that includes individuals who earn too little to be a homeowner, nor the unemployed. The results can also be biased if homeowners are selected into homeownership based on unobserved individual characteristics if these characteristics lead to, for example (better) jobs with higher incomes.[16] In the Netherlands, the largest share of the rental market is rent controlled, especially in the larger cities, and the rent for social housing is based on housing characteristics only, irrespective of the location of the dwelling. Rents, therefore, do not reflect a willingness to pay for living in an area or a valuation of local amenities, as is assumed in hedonic approaches and regional equilibrium models like those in Rosen (1974), Roback (1982). For these reasons, using rents, if available, are not preferred in the present study.

We measure the scale of diversity by the share of immigrants in a city as a city is more diverse if there are overall more immigrants. Because we are also interested in the composition effect of ethnic diversity, we include the so-called diversity index in our

15 We do not look into ethnic diversity at the level of the workplace for individuals in our data set as done by, for example, Möhlmann and Bakens (2015); Trax et al. (2015); Kemeny and Cooke (2018); however, they find that the effect of firm diversity on (firm) productivity is much lower, or not statistically significant, compared to the effect of city-level diversity on productivity.

16 Using transaction prices leads to another selection bias if the sample of houses sold at a specific time and location are of a specific character. For example, smaller houses for starters on the housing market generally have a higher turnover rate than larger, more expensive houses.

regression. In general, the largest cities have the highest shares of immigrants, and the size effect of immigrants is thus very much related to the scale of a city. By disentangling a diversity index that includes all ethnic groups in the immigrant share from a diversity index that distinguishes among groups of migrants, we are able to distinguish between the scale effect of immigrants and their diversity (Ottaviano and Peri, 2006; Alesina et al., 2016) and estimate whether it is the number of immigrants that matter for economic outcomes in our model, or the diversity of immigrants (or both). The diversity index among immigrants for cities shows the probability that two randomly selected immigrant residents in a municipality are from different ethnic groups. The index is defined as follows:

$$D_c = 1 - \sum_{e=1}^{m} (s_{ce})^2, \tag{4.1}$$

where s_{ce} is the share of people from ethnic group e among the immigrants of city c. An index value of 0 indicates that all immigrants living in a city belong to the same ethnic group, whereas all belong to different ethnic groups when the index value is 1.[17] We identify an individual's ethnicity based on the country of birth of the mother, except when the mother is Dutch, in which case the country of birth of the father determines the individual's ethnicity. This definition thus encompasses first- and second-generation immigrants.

The diversity index as given in Equation (4.1) is also calculated for restaurants based on their ethnic background, that is the country of origin of the food served, in order to measure immigrant-induced product diversity. In total, 20 categories of cuisine are distinguished, of which one is considered Dutch (see Supplementary Appendix Table A1). If there are more immigrants in a city, then it is very likely that there are more ethnic restaurants, as shown by Waldfogel (2008); Mazzolari and Neumark (2012), which may have a separate impact on the attractiveness of residential locations from the mere presence of immigrants. Heterogeneity in consumption goods is generally linked to an increasing attractiveness of cities (Glaeser and Mare, 2001). We therefore include this third effect into our estimations.[18]

We take a 10% sample from the full data set and estimate our model using 48,491 observations.[19] The sample is stratified by the municipality of work to ensure the spatial representativeness of our data. Table 1 gives an overview of the variables that we focus on. Given that the municipalities of residence and work can be different for an individual, we compose each variable for the municipality of work and the municipality of residence. Table 1 shows that the level of amenities in the cities of work in the sample and the level of amenities in the cities of residence in the sample are statistically different. Clearly, jobs are clustered in different cities than those that predominantly have clusters of residential houses.

17 To be more precise, the maximum value of the index depends on the number of ethnic groups, m. The maximum value is $1 - 1/m$ and approaches 1 in the limiting case in which m goes to infinity.

18 As is shown by footnote ‘a’ in Table 1, the correlation coefficient of the scale of immigrants and restaurant diversity is larger than the correlation between immigrant diversity and restaurant diversity. We implement robustness checks to look into a possible collinearity problem of including both immigrant share and restaurant diversity.

19 Correctly determining the variance–covariance matrix of a finite mixture model is done by simulation and is therefore rather time consuming. A reduced sample size (10%) facilitates estimation.

Table 1. Descriptives of selected variables[a]

Variables	City of work Mean (St.dev.)	City of residence Mean (St.dev.)	t-value[b]
Wage[c] €/year	39,813 (24,715)		
House price[d] €/m^2		2 051 (664)	
Immigrant share	0.24 (0.13)	0.21 (0.11)	50.77
Immigrant diversity	0.91 (0.03)	0.91 (0.04)	6.41
Restaurant diversity	0.75 (0.12)	0.74 (0.13)	26.59
Restaurants[e]	7.78 (3.71)	7.25 (3.44)	27.13
Museums[e]	0.68 (0.48)	0.69 (0.56)	–4.90
Theaters[e]	0.22 (0.17)	0.20 (0.17)	30.21
Shops (× 10)	13.01 (3.29)	12.51 (3.32)	27.83
Observations	48,522	48,522	

Source: Based on data from Statistics Netherlands, NVM.
[a]The correlation coefficient between Immigrant share and immigrant diversity (restaurant diversity) is −0.07(0.64), and between immigrant diversity and restaurant diversity is 0.11 for the sample of cities of work. The correlation coefficient between immigrant share and immigrant diversity (restaurant diversity) is −0.06(0.59), and between immigrant diversity and restaurant diversity is 0.11 for the sample of cities of residence.
[b]A paired t-test of the equality of means is performed, with $H_0 : \mu_{work} = \mu_{city}$. The means of the independent variables are all statistically significantly different between the city of work and the city of residence.
[c]The yearly wage is given in 2008 prices.
[d]The house price per square meter is given in 2008 prices.
[e]The number of restaurants, museums and theaters are measured as the number per 10,000 inhabitants.

5. Results

We assume a regional model with two types of workers and two types of firms that value high- or low-amenity areas in both the labor and the housing market. This results in four different groups that can be distinguished in our data. Between these four groups, individuals have different preferences for ethnic diversity related to different wages or utility levels.[20] Subsection 5.1 first deals shortly with the common results for all groups [being the set of individual (**X**) and housing (**H**) characteristics in Equations (5.1) and (5.2)]. Subsequently, in subsection 5.2, we focus on the heterogeneous results for the four groups, and subsection 5.3 lays out the ex-post group composition and further explores the possible spatial distribution of the four groups.

5.1. Common results for all groups

The first part of the results, the coefficients β_1 and γ_1 of regression Equations (5.1) and (5.2) which are homogeneously estimated for all four groups, are given in the Supplementary Appendix Tables A2 and A3, respectively. The coefficients of the homogeneously estimated variables are as expected for both regressions. The standard

20 Information criteria show that from a statistical point of view, the optimal number of groups is larger than 4; using more groups, however, does not change our main conclusions. In fact, the robustness checks in Section 6 show that the results are rather robust to the number of groups.

errors of the education dummies in Supplementary Appendix Table A2 are rather small due to the omission of low-income groups. Accordingly, the negative coefficient for the share of highly educated workers in the labor market might also be caused by our sample; one would expect the share of highly educated workers in the labor market to have a positive effect on wages. Diversity (of all ethnic groups including the Dutch) at the neighborhood level[21] is included for the housing price regression, and the impact is negative and statistically significant. This result indicates that neighborhoods with a more diverse population have, all other things being equal, lower housing prices. This result is found in previous research as well, and can be caused by many mechanisms (see e.g. Saiz, 2003; Sá, 2015). It might indicate that a diverse population is related to lower housing prices, but it can also point towards the relationship between immigrants and low-income neighborhoods and deprivation. For the purpose of this article, which is to identify amenities at the city level, we separate the amenity effects at the city level from the neighborhood level by controlling for neighborhood diversity. Estimation of the homogeneous part of the regression excluding neighborhood diversity indeed shows that the coefficients of population diversity at the city level in the heterogeneous part of the regression are in general lower, indicating that failing to control for neighborhood effects decreases the effect of diversity on the city level.

5.2. Group-specific results

Empirically, our estimation results in one large group (Group 3) containing 73% of the individuals in our sample, and three small groups (the size of each group is given in Table 2 and in the Supplementary Appendix Table A4). Group 1 contains about 9%, and Groups 2 and 4 about 7 and 12% of all individuals, respectively. Figure 4 depicts the distribution of the probabilities of the observations assigned to each group (an individual is allocated to the group to which he or she has the highest probability of belonging) and shows how well the groups are defined in terms of heterogeneity between groups and the homogeneity within groups. If an individual has a probability of almost 1 of being in a group and a probability of almost 0 of being in the other groups, then we have perfect heterogeneity between groups and perfect homogeneity within groups. The Whiskerplot in Figure 4 indicates that the within group homogeneity and between group heterogeneity is substantial albeit not perfect. The average probability of being in Group 1 is around 0.7, in Group 2 around 0.8, in Group 3 around 0.6 and in Group 4 around 0.5. Note that with nonrepeated observations, near perfect segmentation is often harder to achieve than with repeated observations. The effectiveness of the finite mixture model estimations to distinguish different groups in the data in terms of their productivity and utility effects of ethnic diversity is thus successful for the first two groups, moderately successful for the third group, while Group 4 seems to be more of a rest group with partly observations that do not fit well in either one of the groups. The posterior probabilities (given in Supplementary Appendix Table A4) show that the number of observations in the data set that have a nonzero probability of being in a given group. In our case, almost every observation in the data

21 Neighborhoods are defined by the Dutch Bureau for Statistics as architectural and historical homogeneously parts of municipalities. Typically, the average population of a neighborhood is about 1000–2000 inhabitants, but it varies considerably with some neighborhoods reaching over 10,000 inhabitants in the larger cities.

Table 2. Regression results FMM with four groups[a]

No. of observations	Group 1 4401		Group 2 3615		Group 3 34,880		Group 4 5626	
Variables	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Wage								
Constant	10.027***	0.011	10.553***	0.019	10.182***	0.010	10.175***	0.010
Immigrant share	−0.027***	0.010	0.033**	0.015	0.039***	0.005	0.010	0.006
Immigrant diversity	−0.003	0.005	0.012	0.010	0.004	0.003	0.018***	0.004
Restaurant diversity	−0.014**	0.007	−0.011	0.013	0.005	0.004	−0.002	0.006
Historic center	0.028*	0.016	−0.003	0.029	−0.002	0.010	0.048***	0.013
Restaurants[b]	−0.008	0.007	0.039**	0.016	0.011**	0.005	−0.016*	0.008
Museums[b]	−0.007	0.005	0.001	0.011	−0.004	0.003	−0.004	0.005
Theaters[b]	−0.014**	0.006	0.028**	0.012	0.002	0.004	−0.012**	0.005
Shops (×10)	0.015**	0.006	−0.008	0.011	−0.014***	0.004	0.002	0.006
Housing price								
Constant	7.235***	0.015	7.600***	0.013	7.428***	0.110	7.410***	0.013
Immigrant share	0.070***	0.007	0.032***	0.008	0.087***	0.005	−0.105***	0.010
Immigrant diversity	0.039***	0.005	0.036***	0.006	0.037***	0.002	−0.002	0.003
Restaurant diversity	0.030***	0.006	−0.027***	0.006	−0.016***	0.003	0.047***	0.006
Historic center	0.003	0.013	0.117***	0.017	0.165***	0.008	0.180***	0.015
Restaurants[b]	0.054***	0.004	0.107***	0.008	0.063***	0.003	0.064***	0.007
Museums[b]	−0.030***	0.004	−0.021***	0.007	−0.009***	0.003	0.011***	0.004
Theaters[b]	0.051***	0.005	0.020***	0.006	0.042***	0.003	−0.014**	0.007
Shops (×10)	−0.064***	0.005	−0.053***	0.007	−0.075***	0.003	−0.018***	0.006

Source: own calculations based on Statistics Netherlands, NVM.
[a]Huber-White robust standard errors are reported. The statistical significance of coefficients is indicated with ***, **, * for the 0.01, 0.05 and 0.1 significance levels, respectively. All variables, except historic center, are standardized.
[b]The number of restaurants, museums and theaters are measured per 10,000 inhabitants.

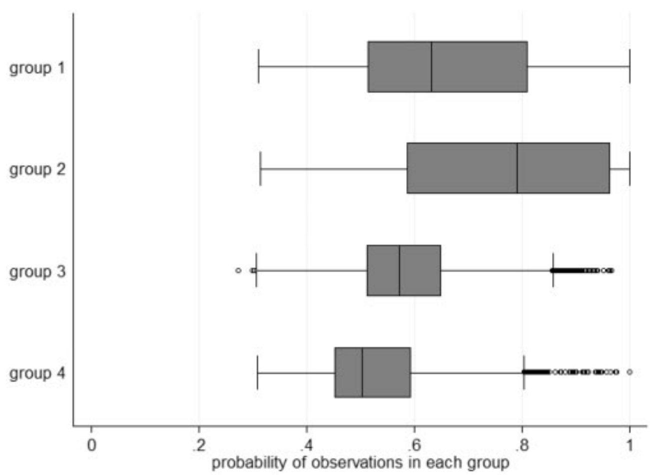

Figure 4. Distribution of probabilities of the observations in each group.

set has a (very small) probability of being in any of the other groups. Based on these descriptives of the fitting of the FMM, we believe that only Group 4 will show less reliable results as the within-group homogeneity is relatively low.

Roback (1982) states that a positive coefficient for ethnic diversity in the labor market indicates net disamenities for workers and that a positive coefficient for ethnic diversity in the housing market indicates net amenities for workers. Ottaviano and Peri (2006) elaborate on this interpretation by showing that a positive coefficient for diversity in both markets signals a positive productivity effect. Firms are only willing to locate to areas with higher land prices, if productivity (and thus wages) is sufficiently high. This implies that workers are willing to pay higher house prices if those prices are off set by higher wages, and there is no specific real-wage effect. A positive coefficient for diversity in the labor market but a negative coefficient in the housing market signals a negative utility effect, because workers need to be compensated for loss of utility by lower house prices and/or higher wages, that is higher real wages. Likewise, a positive coefficient for diversity in the housing market combined with a negative coefficient for diversity in the labor market signals that workers are willing to accept a lower real wage if the utility derived from diversity is positive.

The results of the heterogeneous part of the wage and house price regression are given in Table 2. We mainly focus on the interpretation of the coefficients of the scale, composition and consumer good effect of ethnic diversity because the other amenities are included to control for other possible city characteristics and amenities that explain wages and house prices. We follow the reasoning by Ottaviano and Peri (2006), Roback (1982) as described above to interpret the results as a combined effect in both markets.

Only the scale of ethnic diversity, that is the immigrant share, has a statistically significant effect in both markets for all groups. Groups 2 and 3 derive a positive productivity effect from a higher share of immigrants, while Group 1 derives a positive utility effect and Group 4 a negative utility effect from immigrant share. Group 1 is thus willing to accept a lower real wage if the share of immigrants is higher, while Group 4 requires a higher real wage to compensate for the disamenity they experience from a higher share of immigrants. We find similar results in sign—but not in magnitude—for immigrant diversity although the coefficients in the labor and housing market are only both statistically significant for Group 1. The same holds for the found coefficients for restaurant diversity. Interestingly, the found effect of restaurant diversity does not necessarily coincide with immigrant share or immigrants diversity. For example, where individuals in Group 4 derive a negative utility effect from the immigrant share, they derive a positive utility effect from restaurant diversity.

To complete the analysis of the results, we need to know whether the estimated coefficients for the scale (composition and consumer good effect) of ethnic diversity from the labor and housing market are jointly statistically significant and how large the estimated effects are in terms of implicit prices. To do so, we weigh the housing market coefficients according to the budget share spent on housing. Using the estimated coefficients in Table 2 and the mean income and the mean price per square meter in Table 4, we can calculate the implicit prices of each ethnic diversity effect for the different groups. We have to make some general assumptions about the yearly share of income devoted to paying for housing (i.e. mortgage payments), and the part of the total house price that is the price of land (i.e. that is not explained by dwelling characteristics). Table 3 then shows if the combined effect is statistically significant and

Table 3. Welfare effects of scale, composition and consumer good effect of ethnic diversity[a]

	Implicit price		
	Scale (Immigrant share)	Composition (Immigrant diversity)	Consumer goods (Restaurant diversity)
Marginal[b]			
Group 1	902.53***	163.55	455.22**
Group 2	−2736.58**	−887.27	839.89
Group 3	−1170.25***	−33.82	−233.41
Group 4	−689.82***	−668.33***	217.68

Source: Own calculations based on Statistics Netherlands, NVM.

[a]The implicit prices are calculated based on the calculation given in Roback (1982): $p^* = [k_l(d\log r/\mathrm{d}s) - (d\log w/\mathrm{d}s)]w$, where w is the mean yearly income of each group from Table 4 and k_l is the mean budget share of land for each group based on the mean price per square meter of each group. The budget share of land is calculated by multiplying the yearly expenditures on a mortgage with a 5% interest rate for a 120 m^2 house, with the price of land fixed at 0.25 of the total transaction price.

[b]The implicit prices are given in euros per standard deviation as the variables are standardized in the regression. Significance of the effects are calculated for the null hypothesis that the joint effect of diversity from both markets is zero, against the hypothesis that the effect is not zero. The coefficient on the housing market(β_1), its variance, and its covariance are weighted by k_l, the mean budget share. The t-value of then equals: $k_l * \beta_1 - \beta_2/(\sqrt{\mathrm{var}(\beta_1) * k_l^2 + \mathrm{var}(\beta_2) - 2 * \mathrm{cov}(\beta_1, \beta_2) * k_l})$. The ***, **, * indicate that the null hypothesis is rejected at the 0.01, 0.05 or 0.1 significance level, respectively.

the implicit prices each group is willing to pay for ethnic diversity on a yearly base. We assume a 120 m^2 house with a mortgage interest rate of 5%, and the ratio of the land price to the total price of the house of 0.25.[22]

According to Table 3, Group 1 is willing to pay €903/year for housing for a one standard deviation increase in immigrant share, and an additional €455 for a one standard deviation increase in restaurant diversity. Groups 2, 3 and 4 are willing to pay an additional amount for housing to decrease the share of immigrants, but for different underlying trade-offs. For Groups 2 and 3, this trade-off relates to the increase in wages they experience in areas with higher shares of immigrants, that is they are willing to accept lower real wages to avoid immigrants. Group 4 is willing to pay to avoid immigrants to increase utility. The magnitudes of the effects are about 2–3% of each groups' yearly income. This is rather high in absolute terms but if we take into consideration that interest payments on mortgages are deductible from income taxes, then the implicit prices are likely to be overestimated and to be about 1– 2% of each groups' yearly income.[23]

Overall, it seems that we only find statistically significant results for all groups for the scale of immigrants, and for 80% of the individuals in our sample, this relates to them experiencing higher wages in areas with more immigrants (i.e. a positive productivity externality). For about 9% of the individuals (Group 1), utility is higher if the share of

22 See, for more details, the footnote of Table 3 and Roback (1982).
23 This is the result if we assume that 40% of the costs for housing is exempt.

immigrants is higher and restaurant diversity is higher (consumer good effect). Immigrant diversity is a disutility for about 12% (Group 4) of the individuals in the data. For the other groups, the joint estimates of immigrant diversity in the labor and housing market are not statistically significant. Except for Group 1, restaurant diversity is not statistically significant. If we compare our results to the research by Ottaviano and Peri (2006), Alesina et al. (2016), we find similar results that for the majority of the people in our data, immigrants share and immigrant diversity have a positive correlation with productivity; however, in our research the productivity effect of immigrant diversity is not statistically significant for any of the groups. In this sense, we do not find the same results as Trax et al. (2015); Kemeny and Cooke (2018) who focus on the immigrant diversity effect on productivity and do find positive statistically significant results for this relationship. Our results also show that for a small group of people in our data, the effects of immigrant diversity and immigrant share are not related to positive productivity effects, but related to positive or negative utility effects. Although the housing market regression shows statistically significant results for restaurant diversity, the joint interpretation of these results with those from the labor market indicates that the effect of restaurant diversity is only relevant for a small group of people in our data set.

5.3. Group composition and spatial sorting

By *ex post* facto summarizing the characteristics of individuals in each group (an individual is allocated to the group to which he or she has the highest probability of belonging), we further explore how those groups differ in terms of income and education, but also whether the differences between groups may give a conjecture of spatial sorting or not. Firstly, Table 4 shows that the most distinctive features between the groups are income and geographical concentration. Group 2 has the highest income, which is in line with the finding that this group has higher constant terms in both regressions. Group 1 has relatively lower incomes and education levels,[24] and even though Kemeny and Cooke (2018) find no differences between the effect of diversity on wages for different wage quantiles, the income level might explain why this group does not derive a positive productivity effect from a denser and internationally oriented work location. Groups 3 and 4 are very alike in terms of income and education levels. However, the geographical concentration of Group 4 appears to be different. About 29% of the individuals in Group 4 live in one of the four largest cities in the Netherlands.

Individuals in the different groups in our data are thus most likely not randomly allocated over cities. If the allocation is not random, then differences in the correlations between different measures of ethnic diversity and productivity or utility can be amplified by sorting and the subsequent concentration of specific groups in specific cities. Mapping the over- and under-concentration of the groups at labor market areas (measured at the 3-level of the Nomenclature of Territorial Units for Statistics or

24 We want to stress again that our sample does not include individuals in the commercial or social rent category but only homeowners. The group with lower average education levels and lower average incomes are thus at the lower end of the distribution of these variables for homeowners. From the descriptive statistics, it can be seen that Group 1 is still fairly highly educated and has a high income if compared to the whole of the Netherlands. Our sample of only homeowners leads to this bias.

Table 4. Socioeconomic and demographic group characteristics

Variables	Group 1	Group 2	Group 3	Group 4
Mean wage €/year	28,173	87,219	36,856	36,789
Mean housing price €/m^2	1351	2.951	2047	2044
Mean age	32	36	32	32
% immigrant (first or second generation)	15	13	13	16
% university degree (educated	19	42	28	25
Household type				
% single person	29	20	27	28
% couple with children	29	42	27	26
% couple without children	40	36	45	44
% working and living In same municipality	33	24	30	33
% working and living In same NUTS3 region	52	45	52	55
Average commuting distance incl. Same municipality (km)	35	29	26	23
Average commuting distance excl. Same municipality (km)	52	38	37	34
% working in four largest cities	24	29	25	32
Amsterdam	9	14	10	10
Rotterdam	5	4	5	7
Utrecht	3	7	6	5
The Hague	8	4	4	11
% Living in four largest cities	17	15	16	29
Amsterdam	2	6	5	4
Rotterdam	3	3	3	6
Utrecht	3	4	6	4
The Hague	10	3	2	15

Source: Based on data from Statistics Netherlands, NVM.

NUTS-3 level) by calculating a location quotient (LQ) for each group and the corresponding Moran's *I*, shows that the spatial allocation of individuals over groups is not random.

In Figure 5, over-representation or clustering of a group is given in black, while under-representation is given in light gray. For mapping purposes, we log-linearize the LQ. For the geography of the Netherlands, it is important to know that immigrants are under-represented in the periphery of the country (the northern and southern parts), which has a relatively low population density. In the middle part of the country, the presence of immigrants is average, while most immigrants are clustered in the Randstad, the part of the country that contains the largest cities in the western region. The southern corridor of the Randstad area consists of Rotterdam and The Hague, and the northern corridor consists of Amsterdam and Utrecht. Furthermore, a distinction is often made between different areas in the middle of the country in terms of productivity (number of jobs and sector clusters), abundance of amenities (consumer and natural amenities), and thus in general the attractiveness of the different cities in this area, especially for individuals with a preference for 'urban' surroundings.

As could be expected because of the size of the group, Group 3 has the smallest variation of all groups and is evenly distributed across the country proportional to the

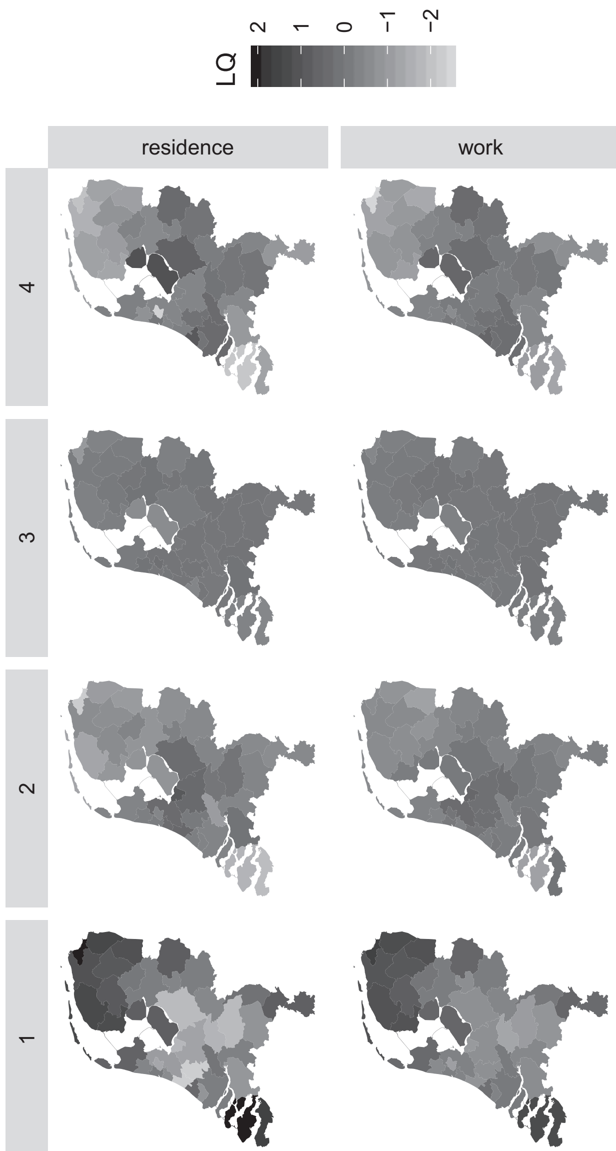

Figure 5. Spatial clustering of groups across NUTS3-regions.

actual population distribution over the Netherlands. This conclusion is supported by the measure of spatial autocorrelation given in Table 5. Moran's *I* for this group is the lowest.[25] There is no strong indication that the individuals in this group would sort into areas based on amenities as measured in this research. Other mechanisms like life-cycle

25 The expected value of Moran's *I* for all groups is −0.026 under the null hypothesis of no spatial correlation, that is spatial randomness.

Table 5. Moran's *I* of Location Quotients[a]

Group	Moran's I Labor market	Housing market
Group 1	0.18	0.16
Group 2	0.16	0.12
Group 3	0.08	0.04
Group 4	0.17	0.08

Source: own calculations based on Statistics Netherlands, NVM.
[a]Moran's *I* is calculated for the log-linearized location quotients, using the inverse of the Eucledian distance between the centroids of NUTS3 regions. The H_0 hypothesis of spatial randomness of location of individuals within a group is tested against the H_1 hypothesis of spatial autocorrelation. All values are statistically significant at the 0.01 significance level.

choices, location path dependency and social ties, or job opportunities probably play a much more vital role in explaining the location of the individuals in this group as is referred to by, for example, Kemeny and Storper (2012).

Groups 1, 2 and 4 show a stronger spatial pattern with moderate, albeit statistically significant, clustering. Group 1 is clustered further away from the economic core of the Netherlands in areas that are considered less abundant in amenities, especially man-made amenities, and that have a lower concentration of immigrants. Group 2 is clustered in the economic centers of the Netherlands in terms of work location, and is residentially clustered in the amenity-rich areas, both in terms of consumer amenities as well as natural amenities. This group lives and works in areas with higher concentrations of immigrants. This is especially true of the northern corridor of the Randstad. Group 4 also lives and works in areas with higher concentrations of immigrants, but this group is more concentrated in the southern corridor of the Randstad and outside of Amsterdam and Utrecht in the north. In this regard, Group 4 seems to be the opposite of Group 2, a difference that is likely to be driven by the result that Group 4, as opposed to Group 2, derives a negative utility from living in cities with a higher immigrant share and diversity.

6. Robustness Checks

To validate our results, we have conducted various robustness checks. A first main concern might be that, as the results are based on four groups, the data actually distinguishe more, or less, groups. Therefore, we estimate our models with 2, 3 and 5 groups (the estimation for five groups converges into four groups). The results of these estimations can be found in the Supplementary Appendix (Tables A10–A15).[26] We find that in all estimations, one large group and several smaller groups are distinguished in the data. For the estimation with two and three groups, the results for the largest group

26 We only report the heterogeneous part of the estimation in these tables. Note that we report the groups as indicated in the results, which means that group numbers are random (Group 3 is not always the largest group, etc.).

are comparable with the largest group in our base regression with four groups. The smaller groups are comparable as well in the sense that there is a group for which the composition and consumer good effect of ethnic diversity are a positive utility effect as opposed to a productivity effect.

In this article, we assume that the location choice of work and residence is interrelated and we therefore estimate the wage and housing price equations simultaneously. To test the validity of this assumption, we estimate the wage and house price regressions separately.[27] Using four groups, the wage regression with the finite mixture model results in convergence to three groups, while the housing price regression has convergence issues. This indicates that the correlation between the two regressions does indeed lead to different results as the interaction between the two is needed to identify unobserved heterogeneity. As work locations are often more clustered than residential locations, our integrated estimation allows for the possibility that individuals that obtain the same wage in the same city of work, may live in different locations with different amenities and house prices, and may therefore have different utility or productivity trade-offs. Again, in the estimations with separate wage and housing price regressions, we find one large group, and several much smaller groups. For the largest group, the wage and house price regression results are comparable to those of the largest group in the base regression. However, the interpretation of the results may differ, as we would interpret the results in terms of a positive utility effect as opposed to a positive productivity effect. The results of the group with the highest constant in each regression is comparable with the group with the highest constant in the base regression (the group with the highest income).

Additionally, we want to be sure our results are not confined by the sample we used in our estimation. As we use a 10% stratified (by place of work) sample from the data set for our estimations, we re-ran the model on two different, stratified, samples from the main data set. The results of these two samples are given in Supplementary Appendix Tables A5–A7. Over the different samples, we consequently find that for most individuals the estimated coefficients have a consistent sign for immigrant share and immigrant diversity, that is if immigrant share has a positive correlation with wages (or house prices), immigrant diversity has a positive correlation with wages (or house prices) as well. However, the coefficients are not always both statistically significant. In these alternative samples, we still find one large group (Group 4 in subsample 1 and Group 3 in subsample 2) with comparable results for the scale, composition and consumer good effect in the housing market. Generally, we thus find that for most individuals in our data set, the scale of immigrant diversity is positively related to productivity, while the positive correlation between productivity and the composition of immigrant diversity is mostly not statistically significantly different from zero. The robustness checks for restaurant diversity show mixed results; the results are not always exactly comparable in terms of sign, but generally restaurant diversity is not statistically significant in the wage regression for most individuals in our data set. The coefficient for restaurant diversity is statistically significant for everyone in the housing price regression.

Finally, a rather substantial concern that needs to be addressed, is a collinearity problem in our estimations that may arise from the correlation between immigrant

27 See the Supplementary Appendix Tables A10–A15 for the results.

share and restaurant diversity. We know that areas with more immigrants have more diverse restaurants but the relationship is not direct, as obviously not all immigrants are restaurant owners, and not all ethnic restaurants are located where immigrants reside. There is thus a multitude of mechanisms that may explain this relationship (some are described in the Introduction section), which we are not able to disentangle in our data set. For the full sample, the correlation coefficient between immigrant share and restaurant diversity (immigrant diversity) is 0.64 (–0.07), and between immigrant diversity and restaurant diversity is 0.11 for the sample of cities of work.[28] The correlation coefficient between immigrant share and restaurant diversity (immigrant diversity) is 0.59 (–0.06), and between immigrant diversity and restaurant diversity is 0.11 for the sample of cities of residence. The correlation between immigrant share and restaurant diversity is substantially large to cause concern for (multi)collinearity. Collinearity may cause two problems for our regression results. Firstly, standard errors are higher if collinearity is present and the chance of a type II error (false negative) for some variables increases. Second, if variables are highly correlated, estimates of their individual effects on the dependent variable become less reliable and more unstable.

If we look at the correlation matrices for immigrant share and restaurant diversity for the different FMM groups in our estimation, then we see that there are small differences in the correlation between immigrant share and restaurant diversity between the groups (Supplementary Appendix Table A8). The differences between the groups are not large enough to conclude that it is an issue for only some groups but not for others, but Group 4 seems to have the largest concerns for collinearity. Collinearity in the data between immigrant share and restaurant diversity is a bigger problem for the city of work than the city of residence. The differences in these correlation coefficients between the city of work and the city of residence of about one-tenth point seem to impact part of our results. If we run the base regression of Table 2 without restaurant diversity, then the standard errors for immigrant share decrease substantially in the wage regression and the coefficients for immigrant diversity become statistically significant (Supplementary Appendix Table A10). Although the standard errors are lower, the estimated coefficients of immigrant share do not change substantially compared to the base regression and we are now less concerned that these results are unstable or unreliable. In addition, the estimates for all the other control variables are comparable to the base regression. Without restaurant diversity, immigrant diversity becomes statistically significant in the wage regressions and we find a positive productivity effect of immigrant diversity for Groups 2 and 3, and a positive utility effect for Group 1. This may point toward type II errors for immigrant diversity in the base regression even though the correlation between immigrant diversity and restaurant diversity or immigrant share is low. Immigrant diversity then has a positive correlation with productivity and utility for some groups, but the size of the effect is much smaller than that for immigrant share. The estimations for Group 4 seem to suffer most from possible collinearity, which is probably also related to the fact that this group is considered a ‘rest’ group with lower within-group homogeneity of the observations.

28 The correlation coefficient for immigrants share and restaurant diversity for the city of work is comparable to the correlation coefficient for immigrant share and immigant diversity in Trax et al. (2015).

Given the possible mechanisms underlying the effects of immigrants on wages and housing prices combined with correlation coefficients between immigrant share and restaurant diversity of 0.59 and 0.68, there is a collinearity problem and the estimations without restaurant diversity indeed impact the results for some groups. However, the collinearity is not large enough to conclude that immigrant share and restaurant diversity measure the same relation in our data, and omitting restaurant diversity may result in a specification error and overestimation of the effect of immigrant diversity on utility or productivity. However, this clearly also calls for more research that is better able to directly measure the impact of these different mechanisms on utility.

7. Conclusions

This article analyses the differences between individuals in terms of the utility and the productivity derived from the scale, composition and consumer good effect of ethnic diversity. We estimate a latent class model in which individuals are endogenously assigned to groups based on these differences. Our article contributes to the existing literature by modeling and estimating the location of work and residence of workers simultaneously, taking into account unobserved heterogeneity in preferences and the subsequent possibility of spatial sorting of individuals based on these preferences. Because we estimate the effects on both the labor and housing market, we can interpret the regression results in terms of a dominant utility or productivity effect of ethnic diversity.

We find one large group and three small groups of (within group) homogeneous individuals. For most individuals in our data set, the immigrant share has a positive productivity effect. So, working in cities with a larger share of immigrants is associated with higher workers' wages, leading to higher housing prices. For one small group, the consumer good effect in the form of restaurant diversity has a positive amenity affect; these workers value living in areas with a large diversity in cuisines. The sizes of these ethnic diversity effects differ between the four groups, but in terms of implicit prices the differences are moderate and do not exceed 1–2% of net yearly income.

The groups we identified differ significantly in their composition, most pronounced in terms of income levels, education and to a much smaller extent spatial concentration, which seem to be the individual differences that matter most in revealing preferences for immigrant composition and induced amenities. Based on geographical clustering and a measure of spatial autocorrelation, we find evidence that only the small groups sort themselves into specific and distinct locations in the Netherlands based on amenities. However, for the majority of our sample ($\sim$70%), no evidence for spatial sorting can be found for the scale, composition and consumer good effect of ethnic diversity. Based on this analysis, we conclude that these amenities do not seem to play a (large) role for sorting and it is more likely that individuals sort over locations based on life-cycle choices, social ties and job opportunities, as is described for the USA by Kemeny and Storper (2012), and by Ellis and Goodwin-White (2006) for immigrant-specific location decisions. The results are robust against checks for the number of groups, and checks that simultaneously estimated regression give different results for the wage and rent regressions. The estimated FMM is fairly successful in identifying different homogeneous groups within the data although panel data would be preferred for the best performance of a FMM. Based on the robustness checks, we are confident that it is predominantly the scale of ethnic diversity that impacts productivity or utility, and that, at the city-wide level, the composition of immigrants and the consumer good effect are much less significant.

Both the association between ethnic diversity and productivity and utility and the heterogeneity of these effects between the different groups are moderate in an absolute sense. Part of these moderate findings may be due to the reason that we cannot include individuals in the (social) rent sector, and therefore cannot include individuals at the lower end of the income and education distribution. The description of individual characteristics shows that income, and to a certain extent, location are the most distinct features between the groups, and excluding the rental sector disproportionally affects the distribution of these variables in our data set. Additionally, groups with higher incomes (and thus individuals with different education levels) are generally considered to have a higher mobility and are more likely to move into larger cities. This further restricts the generalization of our results and a clear identification of heterogeneous groups for the whole of the Netherlands.

In this article, it becomes clear that more research is needed to identify the exact scale, in combination with the exact mechanisms at that scale, at which the effect of immigrant diversity might be at play. Immigrant diversity or consumer good effects may not play a large role at the city-wide level, but within cities they may be much more important for utility. Individuals are not randomly distributed within cities and not all individuals within the same city are exposed to the same level of ethnic diversity. The amenity landscape of ethnic diversity can be very different in different parts of the same city. Within-city allocation and the effects of ethnic diversity on utility then become an important research question [see e.g. Davis et al. (2017), Bakens et al. (2018)].

Supplementary material

Supplementary data for this article are available at *Journal of Economic Geography* online.

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